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FACE RECOGNITION USING CCA ON NONLINEAR FEATURES

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ABSTRACT

The face recognition (FR) system plays a vital role in commercial & law enforcement applications. Image resolution is an important factor affecting face recognition performance. The performance of face recognition system degrades by low resolution of face images. To address this problem, a super resolution (SR) method was introduced by Hua Huang and Huiting He [7], which uses Canonical correlation analysis (CCA) [8], [9] to establish the super resolution subspaces between the principal component analysis (PCA) based features of HR & LR face images. However finding nonlinear relations among features can increase the descriptive power of the data and may result in increase of recognition rate. In this paper a kernel-PCA (KPCA) is applied to extract base features over which CCA is used to obtain super resolution features. The implementation of SR Method using KPCA is compared with the PCA approach of the above referred super resolution method for LR face images, and found an increase of 1.25% (96.87%-95.62%) for ORL Database and 1.5% (94.50%-93.00%) for UMIST Database in recognition.

KEYWORDS: *Kernel-principal component analysis, Canonical correlation analysis, Face recognition, Radial basis function, Super resolution.*

I. INTRODUCTION

Although human beings can easily detect and identify faces in a scene, it is very challenging for an automated system to achieve such objectives. Face recognition has drawn great attention in recent decades, due to its wide range commercial and law-enforcement applications [1]. The challenges become more profound when large variations exist in the face images at hand, e.g., variations in illumination conditions, viewing directions or poses, facial expression, aging, and disguises such as facial hair, glasses, cosmetics and scarves. Despite of these challenges, face recognition has drawn wide attention from researchers in areas of machine learning, computer vision, pattern recognition, neural networks, and so on. Super resolution methods are used for LR Face recognition [2], [3], [4], [5], [6]. In this paper, this work mainly focus on improving the recognition performance in the case where only a single face “snapshot” of LR is available.

For feature extraction, linear PCA features of HR and LR face image sets are used [7], it gives better recognition rate. To further increase recognition rate, nonlinear form of PCA i.e., “KPCA” is used based on integral operator kernel functions. The features are calculated effectively based on kernel-trick [13].And then apply the RBF-based mapping to build the regression model between the features of HR and LR face images in the coherent subspace by taking advantages of the salient features of RBF regression such as fast learning and generalization ability [14],[15],[16],[17]. RBF-based mappings [11] are built in the coherent subspaces, which favor the nearest neighbor (NN) classifier, which make the neighbors belonging to the same class as close as possible.

The rest of this paper is organized as follows. In Section 2, the system outline of Face recognition using CCA on nonlinear features (i.e., KPCA method) is introduced. Section 3 gives brief introduction of PCA algorithm and implementation of SR method for face recognition using KPCA is introduced. Section 4 gives testing phase for face recognition and followed by Result observation & Discussion in Section 5. Section 6 concludes this paper.

II. SYSTEM OUTLINE

Figure 1 provides the system outline of the proposed method that super-resolves features for recognition. This approach is divided into training and testing phases. The corresponding HR and LR face image sets are used for training to obtain the base vectors of CCA transformation and the parameters of RBF regression.

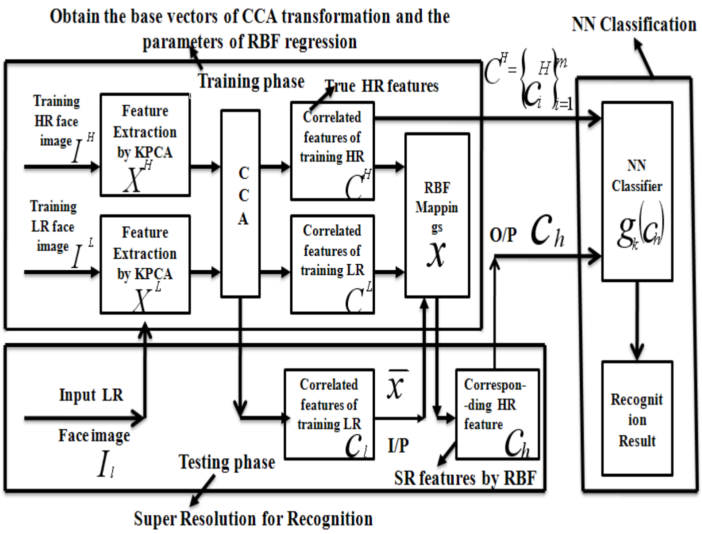

Figure 1. Implementation of Super-Resolution Method for Face Recognition using KPCA

In the testing stage, first it calculates the KPCA feature vector for a given LR image and projects the KPCA features into the coherent subspace using the learnt base vectors. Hence, the SR coherent feature corresponding to the given input LR face image can be obtained by simply applying the learnt RBF mappings. And, an NN classification [16] is performed on these super-revolved features for face recognition.

The problem of SR of feature domain for face recognition is formulated as the inference of the HR domain feature C_h from an input LR image I_l, given the training sets of HR and LR face images $I^H = \{I_i^H\}_{i=1}^{m} = [I_1^H, I_2^H, \ldots\ldots, I_m^H]$ and $I^L = \{I_i^L\}_{i=1}^{m} = [I_1^L, I_2^L, \ldots\ldots, I_m^L]$ where m denotes the size of the training sets. The LR images with the size of 8×8 (for ORL database) and 11×14 (for UMIST database) pixels are generated by the operation of smoothing and down sampling of HR 32×32 (for ORL database) and 46×56 (for UMIST database) images [6]. The face images of one individual in ORL and UMIST databases are shown in Figure 2 and Figure 3.

Figure 2. Face images of one individual in ORL database. (a) HR training face images with size 32×32. (b) LR training face images with size 8×8. (c) LR input face images with size 8×8.

Figure 3. Face images of one individual in UMIST database. (a) HR training face images with size 46×56. (b) LR training face images with size 11×14. (c) LR input face images with size 11×14.

The dimension of the image data, which is much larger than the number of training images, leads to huge computational costs. So, the holistic features of face images are obtained by KPCA.

III. IMPLEMENTATION OF SR METHOD FOR FACE RECOGNITION USING KPCA

The main idea of PCA technique is to project the samples over a subspace which maximizes the variance and minimizes the error. It is readily performed by solving an Eigenvalue problem [12], or by using iterative algorithms which estimate principal components [7]. This is done by selecting the eigenvectors corresponding to maximum eigenvalues called Principal Components of the covariance matrix. Due to huge dimensionality (UMIST - individual face image of size - 112×92) of face images it becomes intractable to compute the eigenvectors directly. So, the holistic features of face images are obtained by classical PCA, which represents a given face image by a weighted combination of eigenfaces is given by

$$x_i^H = (B^H)^T\left(I_i^H - \mu^H\right) \tag{1}$$

Where μ^H the corresponding mean face of HR training face is images and x_i^H is the feature vector of face image I_i^H. B^H is the feature extraction matrix obtained by the HR training face images and is made up of orthogonal eigenvectors of $\left(\hat{I}^H\right)^T \times \hat{I}^H$ corresponding to the eigenvalues being ordered in descending order, where $\hat{I}^H = \left\{\hat{I}_i^H\right\}_{i=1}^{m} = [(I_1^H - \mu^H), (I_2^H - \mu^H), \dots, (I_m^H - \mu^H)]$. Similarly, the feature of LR face image is represented as

$$x_i^L = (B^L)^T\left(I_i^L - \mu^L\right) \tag{2}$$

Where B^L and μ^L are the feature extraction matrix and the mean face obtained by LR training face images, respectively. Then, PCA feature vectors of HR and LR training sets as

$$X^H = \left\{x_i^H\right\}_{i=1}^{m} \epsilon\, R^{p\times m} \tag{3}$$

$$\text{and } X^L = \left\{x_i^L\right\}_{i=1}^{m} \epsilon\, R^{q\times m} \tag{4}$$

The above process of this is based on PCA feature.

Instead of linear PCA [7], [12], KPCA does extract features [13] which are more useful for classification purpose. KPCA has the advantages that (1) it doesn't require nonlinear optimization but the solution of an Eigenvalue problem and (2) by the possibility to use Gaussian kernel it comprises a fairly general class of nonlinearities that can be used.

3.1 Kernel-PCA Feature Extraction

To understand the utility of KPCA, particularly for clustering, observe that, while N images cannot in general be linearly-separated in $d < N$ dimensions, they can almost always be linearly separated in $d \geq N$ dimensions. That is, given N images x_i, map them to an N-dimensional space with

$$\Phi(x_i) = \delta_{ij} \tag{5}$$

where Φ: $\mathrm{R^d} \rightarrow \mathrm{R^N}$ and δ_{ij} is the Kronecker delta. This Φ creates linearly independent vectors, so there is no covariance on which to perform eigendecomposition explicitly as in linear PCA [7]. In KPCA, a non-trivial, arbitrary Φ function is chosen i.e., never calculated explicitly, allowing the possibility to use very high dimensional Φ's, it's very difficult to evaluate the data in that space. In 'feature space', the N-by-N kernel is defined as

$$K = k(x, y) = \big(\Phi\,(\mathrm{x}), \Phi\,(\mathrm{y})\big) = \Phi\,(\mathrm{x})^T \Phi\,(\mathrm{y}) \tag{6}$$

This represents the inner product space of the otherwise intractable feature space. The dual form that arises in the creation of a kernel allows us to mathematically formulate a version of PCA in which it's very difficult to solve the eigenvectors and eigenvalues of the covariance matrix in the Φ(x)-space. The N-elements in each column of K represent the dot product of one point of the transformed data with respect to all the transformed points. To evaluate the dot product (i.e., projection) from a point in the feature space Φ (x) onto the k^{th} principal component V.

$$\mathrm{V}^{\mathrm{k}^{\mathrm{T}}} \Phi\,(\mathrm{x}) = \left(\sum_{i=1}^{N} a_i^k\, \Phi(x_i)\right)^T \Phi\,(\mathrm{x}) \tag{7}$$

Note that $\Phi(x_i)^{\mathrm{T}}\Phi$ (x) denotes dot product, which is simply the elements of the kernel K. It seems all that's left is to calculate and normalize the a_i^k by $N\lambda a = Ka$. It is computationally intensive to compute the eigenvectors of covariance matrix, because of high dimensional feature space (possibly infinite) and also as mapped samples $\Phi(x_i)$ are not directly accessible. However the first $\mathrm{m} \leq \mathrm{N}-1$ most significant eigenvectors of covariance matrix corresponding to nonzero eigenvalues can be indirectly derived from the eigenvectors of $\mathrm{A^T A}$ (refer Section 3). Computing $\mathrm{A^T A}$ which is same as eigenvectors of centered kernel matrix ($i.e.,$ kernel trick K_cntr) [13] is defines as

$$K\_cntr = K - I_N{}^*K - K^*I_N + I_N{}^*K^*I_N \tag{8}$$

where I_N denotes a N -by- N matrix for which each element takes value $1/_N$. Considering two classes r, c consisting of N_i samples each, an N -by- N dot products matrix, which represents the inner product space. Consider a Gaussian kernel:

$$K = k(x,y) = e^{\frac{-\|data(:,r)-data(:,c)\|^2}{2\sigma^2}} \tag{9}$$

i.e., this kernel is a measure of closeness, equal to 1 when the points coincide and equal to 0 at infinity. Where $data$ is HR/LR face images. To normalize the eigenvectors of K, this can be done by solving the eigenvector equation

$$I_N = ones\left(\frac{\left(size(k,2), size(k,2)\right)}{size(k,2)}\right) \tag{10}$$

Then, KPCA feature vectors of HR and LR training sets [13] is nothing but eigenvectors of K_cntr is defined as

$$X^H = \{\, K\_cntr^H\}\,{}_{i=1}^{m} \,\epsilon\, R^{p\times m} \tag{11}$$

And $$X^L = \{K\_cntr^L\}\,{}_{i=1}^{m} \,\epsilon\, R^{q\times m} \tag{12}$$.

The following process of this is based on KPCA feature.

3.2 Coherent Features

In order to learn the relationship between HR and LR feature vectors more exactly, then apply CCA [8], [9], [10]. Then, the more exact coherent SR features can be obtained for recognition in the coherent subspace. Specifically from the KPCA feature training sets X^H and X^L, first subtract their mean values $\overline{X}^H$ and $\overline{X}^L$ respectively, which yields the centralized data sets $\hat{X}^H = [\hat{x}_1^H, \hat{x}_2^H, \ldots\ldots, \hat{x}_m^H]$ and $\hat{X}^L = [\hat{x}_1^L, \hat{x}_2^L, \ldots\ldots, \hat{x}_m^L]$. CCA finds two base vectors V^H and V^L for datasets $\hat{X}^H$ and $\hat{X}^L$ in order to maximize the correlation coefficient between vectors $C^H = (V^H)^T\hat{X}^H$ and $C^L = (V^L)^T\hat{X}^L$.The correlation coefficient is defined as

$$\rho = \frac{E[C^H C^L]}{\sqrt{E[(C^H)^2]E[(C^L)^2]}} = \frac{E\left[(V^H)^T\hat{X}^H\left(\hat{X}^L\right)^T V^L\right]}{\sqrt{E\left[(V^H)^T\hat{X}^H\left(\hat{X}^H\right)^T V^H\right]E\left[(V^L)^T\hat{X}^L\left(\hat{X}^L\right)^T V^L\right]}} \tag{13}$$

Where $E[.]$ denotes mathematical expectation. To find the base vectors V^H and V^L, define $C_{11} = E\left[\hat{X}^H\left(\hat{X}^H\right)^T\right]$ and $C_{22} = E\left[\hat{X}^L\left(\hat{X}^L\right)^T\right]$ as the within set covariance matrices of $\hat{X}^H$ and $\hat{X}^L$ respectively, while $C_{12} = E\left[\hat{X}^H\left(\hat{X}^L\right)^T\right]$ and $C_{21} = E\left[\hat{X}^L\left(\hat{X}^H\right)^T\right]$ as their between-set covariance matrices. Then compute

$$R_1 = C_{11}^T\, C_{12}\, C_{22}^T\, C_{21} \quad (14) \quad \text{and}$$
$$R_2 = C_{22}^T\, C_{21}\, C_{11}^T\, C_{12} \quad (15)$$

V^H is made up of the eigenvectors of R_1 when the eigenvalues of R_1 are ordered in descending order. Similarly, the eigenvectors of R_2 compose V^L [9]. Then obtain the corresponding projected coefficient sets $C^H = \{C_i^H\}\,{}_{i=1}^{m} \,\epsilon\, R^{p\times m}$ and $C^L = \{C_i^L\}\,{}_{i=1}^{m} \,\epsilon\, R^{q\times m}$ of the KPCA feature sets X^H and X^L projected into the coherent subspaces using the following base vectors

$$C^H = (V^H)^T\hat{X}^H \quad (16)$$
$$C^L = (V^L)^T\hat{X}^L \quad (17)$$

As there exists a coherent intrinsic structure between the HR and LR nonlinear feature sets X^H and X^L, the correlation between the two sets C^H and C^L is increased [10] and their topological structures are more coherent after the transformation. Then, the relationship between HR and LR features is more exactly established in the CCA subspace.

3.3 Nonlinear Mappings between the Coherent Features of HR and LR Face Images

As the coherent subspace is obtained, the nonlinear mapping relationship between the coherent features of HR and LR will be learned by the training features [11]. So, apply RBF to construct the mapping relationship. RBF uses radial symmetry function to transform the multivariate data approximation into the unary approximation problem. The form of RBFs used to build up function continuous approximations [12] is

$$f_i(.) = \sum_{j=1}^{m} w_i.\varphi\left(\left\|C^H(i) - C_j(i)\right\|\right) \quad (18)$$

Where the approximating function$f_i(.)$ is represented as a sum of m RBF's $\varphi(.)$, each associated with a different center$C_j(i)$, and w_i is the weighting coefficient. The form has been particularly used in nonlinear systems [14]. In implementation, apply multi-quadric basis function

$$\varphi(.) = \sqrt{\left(\left\|C^L(i) - C_j(i)\right\|\right)^2 + 1} \quad (19)$$

In order to apply RBFs, first train the weighting coefficients by training coherent features of HR and LR face images. The matrix form of RBFs in (18) is represented as $F = W.\varphi$, specifically

$$[f_1,..,f_m] = [w_1,..,w_m]\begin{bmatrix} \varphi.(\|t_1 - t_1\|)..\varphi.(\|t_m - t_1\|) \\ \cdots \quad \cdots \quad \cdots \\ \varphi.(\|t_1 - t_m\|)..\varphi.(\|t_m - t_m\|) \end{bmatrix} \quad (20)$$

Then, the weighting coefficient matrix W is solved as

$$W = F.inv(\varphi) \quad (21)$$

by setting $F = C^H$and $t_i = C_i^L$. Note that, since it is not always invertible, we need to perform a regularization operation, i.e.,$\phi + \tau I$, where τ is set to a small positive value such as $\tau = 10^{-3}$, and I is the identity matrix. Based on the trained RBFs, the SR coherent features of a given LR coherent features can be obtained [7].

IV. TESTING PHASE

Given an LR face image I_l, the KPCA [13] feature vector x_l of the input face image is computed by using the N-by-N Gaussian kernel. Use the kernel-trick K_cntr^L (taken from training phase-Section 3.1).

$$x_l = (K\_cntr^L)^T(I_l - \mu^L) \quad (22)$$

In this approach, recognition process is done in the coherent subspace [9]. So, the KPCA feature vector x_l is transformed to the coherent subspace as

$$c_l = (V^L)^T\left(F_q - \overline{x}^L\right) \quad (23)$$

The coherent HR feature vector $\left(c_{hq}\right)$ corresponding LR feature is obtained by feeding the coherent feature of the LR face image C_l to the trained RBF mapping [11] in (18).

$$c_{hq} = W.[\varphi.(C_1^L, C_l), \ldots.., \varphi.(C_m^L, C_l)]^T \quad (24)$$

Finally, apply the coherent feature c_{hq} and $C^H = \left\{C_i^H\right\}_{i=1}^{m}$for recognition based on the NN classification [16] with L_2 norm

$$g_k\left(c_{hq}\right) = min\left(\left\|c_{hq} - c_{ik}^H\right\|_2\right) \quad i = 1,2,\ldots,m \quad (25)$$

Where c_{ik}^H represents the i^{th} sample in the k^{th}class in C^H.

V. RESULT OBSERVATION & DISCUSSION

To analyze the performance of the super resolution method using nonlinear feature extraction KPCA, Two sets of experiments are performed on two different well-known face image databases: ORL [17] and UMIST [18]. The databases are chosen so as to cover a wide range of possible variations of face images due to expression illumination and pose. The ORL database is used to evaluate the performance of the system under conditions where slight pose, imprecise face alignments and expressions vary. The UMIST database is used to examine the system performance when there is an extreme facial pose variation. In experiments with each database, tests are also performed with the training condition of varying discriminant features (feature dimensions). The average recognition rates are tabulated when all the discriminant vectors are considered. The KPCA [13] is also compared with existing method PCA [7].

To start the FR experiments, each one of the two databases is randomly partitioned into a training sets and a test sets with no overlap between the two. The partitions of the databases are done as follows: ORL includes 40 individuals, and each has 10 different face images. For each individual in ORL database, randomly chosen different sizes of Training sets (2 samples per class, 3 samples per class, 5 samples per class, 7 samples per class, 8 samples per class) and corresponding testing sets (8 samples per class, 7 samples per class, 5 samples per class, 3 samples per class, 2 samples per class) are formed. Similarly for UMIST database (Uneven database) consists of 564 images of 20 individuals. It is uneven database but consider each has 20 different face images. For each individual in UMIST database randomly chosen different sizes of Training sets (5 samples per class, 7 samples per class, 10 samples per class, 13 samples per class, 15 samples per class) and corresponding testing sets (15 samples per class, 13 samples per class, 10 samples per class, 7 samples per class, 5 samples per class) are formed. In order to evaluate the recognition rate accurately, recognition rates are averaged over 2 runs and are tabulated in Table 1 and 3 for ORL and UMIST respectively using all the discriminant features. Table 2 and 4 shows the recognition rates with varying feature dimensions with 5 samples per ORL database and 15 samples for class for UMIST database. From these results the recognition rate increases with an increase in number of training images. Comparing the PCA feature extraction the nonlinear approach KPCA achieves higher recognition rates under the variations of expression, pose and a wide range of multiview face images.

Table 1. The Average Percentage of face recognition rates over two runs for the ORL database

Number of Training Samples/class	**Existing PCA**	**Implemented *Kernel-PCA (KPCA)**
2	88.28	92.28
3	89.29	93.93
5	94.50	95.50
7	94.58	96.25
8	**95.62**	**96.87**

Table 2. The Percentage of Recognition Results with different feature dimensions for the ORL database

Dimension	**20**	**30**	**40**	**50**	**64**
***Kernel-PCA**	**91.75**	**92.25**	**93.00**	**93.75**	**95.50**
Existing PCA	**90.25**	**91.50**	**91.50**	**92.50**	**94.50**
CLPM [7]	84.50	87..50	89.00	89.50	**91.50**
Wang’s [7]	86.50	89.50	90.00	90.50	**91.00**
Gunturk’s [7]	85.50	88.00	90.00	**91.00**	**91.00**
PCA-RBF[7]	87.00	88.00	88.50	88.50	**89.00**
RBF-PCA[7]	85.00	87.50	**88.00**	**88.00**	**88.00**
LR-PCA [7]	81.50	83.50	84.00	84.00	**84.50**
HR-PCA [7]	88.00	89.50	90.50	**91.50**	**91.50**

Table 3. The Average Percentage of face recognition rates over two runs for the UMIST database

Number of Training Samples/class	**Existing PCA**	**Implemented *Kernel-PCA (KPCA)**
5	88.50	90.17
7	89.27	91.15
10	91.25	92.75

13	92.86	93.93
15	**93.00**	**94.50**

Table 4. The Percentage of Recognition Results with different feature dimensions for the UMIST database

Dimension	50	60	70	80	90	100
***Kernel-PCA**	**91.50**	**91.50**	**92.50**	**93.00**	**93.50**	**94.50**
Existing PCA	**89.50**	**90.50**	**92.00**	**92.00**	**92.50**	**93.00**
CLPM [7]	81.00	81.00	86.00	87.00	87.00	**88.00**
Wang's [7]	88.00	88.00	89.00	89.00	**91.00**	**91.00**
Gunturk's [7]	44.00	44.00	45.00	46.00	47.00	**49.00**
PCA-RBF[7]	87.00	87.00	88.00	89.00	**91.00**	**91.00**
RBF-PCA[7]	90.00	89.00	91.00	91.00	**91.00**	**91.00**
LR-PCA [7]	86.00	86.00	87.00	87.00	88.00	**90.00**
HR-PCA [7]	90.00	91.00	91.00	91.00	91.00	**92.00**

VI. CONCLUSION

The face recognition system is degrading its performance by LR images. To address this problem, an SR method in the feature domain for face recognition was proposed in this paper. By the use of integral kernel functions, it can efficiently compute principal components in high-dimensional feature spaces. CCA transformation to the KPCA feature sets of HR and LR face images in order to find the coherent feature subspaces. A non-linear mapping between HR/LR features can be built by RBFs with lower regression errors in the coherent feature space than in the KPCA feature space [13]. Hence, the SR coherent feature corresponding to an input LR face image was obtained by simply applying the learnt RBF mappings. And, face identity can be obtained by feeding these SR features to a simple NN classifier. Compared to other feature domain SR methods, the proposed method is more robust under the variations of expression, pose and down-sampling rate and has a higher recognition rate. CCA was applied to the KPCA features to form the coherent features for recognition, but it is applicable to other holistic face recognition features such as independent component analysis [2] and discrete cosine transform features [19], which might improve the recognition performance further.

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